Foreign Institutional Investors and Corporate Carbon Emissions: Evidence from China

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Abstract

This paper examines the effect of qualified foreign institutional investors (QFIIs) on the reduction of corporate carbon emissions in China. Using a sample of 1,977 Chinese publicly listed firms over the period 2012-2018, I find that the presence of QFIIs reduces firms' carbon emissions. This association is stronger when QFIIs are domiciled in countries with higher social norms (i.e., better environmental performance and higher regulatory quality), suggesting the importance of social motivation behind QFIIs' push for carbon reduction. I provide further evidence that QFIIs' engagement can be realized through two mechanisms: voting power and common ownership. In addition, I also find that the effect of QFIIs' decarbonization is more pronounced when firms operate in the inland provinces with higher exposures to air pollution, and when QFIIs are domiciled in Asia and Australasia with closer geographical distance to China.

Keywords: Qualified foreign institutional investors (QFII); Carbon emissions; Social norm; Voting power; Common ownership

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1. Introduction

In the era of globalization, foreign institutional investors have become increasingly important for global economy in recent years. As major players in global financial markets, they tend to build and maintain diversified portfolios by holding a large number of companies across the world to reduce volatility risk (Bena et al., 2017). Unlike domestic institutions which often have affiliations with local firms they invest in, foreign institutional investors are more likely to be independent of a solo firm's incumbent management and are less tolerant to manager opportunism (Gillan and Starks, 2003; Ferreira and Matos, 2008; Bena et al., 2017). They could also bring forward the knowledge, skills and global networks to address corporate matters of investee firms (Luong et al., 2017). Because of these marked positive features, foreign institutions are generally viewed as firms' value creators, through which they can promote long-term investment (Bena et al., 2017), stimulate corporate innovation (Luong et al., 2017; Bena et al., 2017), drive corporate social responsibility (Dyck et al., 2019; Li et al., 2020), accelerate convergence in global financial reporting (Fang et al., 2015), and affect earnings management as well as smoothing activities (Lel, 2019; Wu et al., 2015). Previous literature on the governance function of foreign institutional investors either focuses on the US market or uses a cross-country setting. Yet, the evidence of these foreign investors' role in emerging markets is relatively sparse (Li et al., 2021).[1] Moreover, following the 2015 Paris Agreement, there is a growing concern about environmental pollution and sustainability issues, such as climate change. As the negative externality of greenhouse gas emissions makes it challenging for establishing a top-down cross-country climate cooperation, corporate governance is seen as an alternative strategy for addressing environmental issues, particularly slashing emissions (Stern, 2008; Azar et al., 2021). Given the growing prevalence of sustainable investment and ESG activism in the context of global warming (Dimson and Karakas, 2015), this paper investigates the influence of foreign institutions, an important element of corporate governance, on dealing with a detailed cutting-edge issue, the reduction of carbon emissions embedded in the ESG governance.

China provides an ideal setting to study whether foreign institutions help investee firms reduce their carbon emissions for following two reasons. First, China has been one of the highest global carbon emitters and chronically experienced severe environmental pollution, despite its miraculous achievement in the economy. According to a research report released by

[1] There is some literature supporting the view that (qualified) foreign institutional investors can function as a governance mechanism in the Chinese context (Huang and Zhu, 2015; Li et al., 2015; Wu et al., 2015; Li et al., 2020; Chen et al., 2013; Li et al., 2021; Kim et al., 2020; Xiong et al., 2021; Huo and Ahmed, 2017).

the Rhodium Group, an independent research provider, China alone emitted around 27% of the world's greenhouse gases in total in 2019, which surpassed those emitted by the OECD and all EU member states.[2] In 2020, China became the largest polluter around the world by releasing 10.67 billion metric tons of carbon emissions. In this context, Chinese policymakers have implemented a series of policies aligned with the 2015 Paris Agreement to curb emissions and fight against environmental degradation, such as announcing the commitment to hit carbon emission peak before 2030 and reach carbon neutrality before 2060.[3] To support the transition towards net-zero emissions, a paramount initiative is to facilitate sustainable financing by attracting those experienced international institutional investors and promoting their engagement with local firms. Second, as a milestone of China's global financial integration, the launch of the Qualified Foreign Institutional Investor (QFII) scheme in 2002 has attracted a substantial number of international institutional investors piling into the Chinese capital markets.[4] One important objective of this ongoing reform is to improve firm-level governance structure through allowing domestic firms to benefit from international investment practices. Environmental issues relating to greenhouse carbon dioxide emissions are crucial aspects of corporate governance from the view of stakeholders. Given the pivotal role of QFIIs in China, exploring the effectiveness of foreign investors on corporate carbon reduction is meaningful, as it echoes the call for urgent action from these leading global institutions on climate change.

I hypothesize that QFIIs are able to push Chinese firms to reduce corporate carbon emissions. The conjecture is motivated by Azar, Duro, Kadach and Ormazabal's (2021) findings that large institutional investors (the Big Three) engage with worldwide firms on environmental issues (i.e., carbon reduction). As an importance force in China, I expect QFIIs can exert their influences on firms' decarbonization for at least two reasons. First, as climate risk materializes, the values of firms within the portfolio managed by QFIIs are largely affected by the extent to which firms' business models are exposed to carbon risk. Being aware of the potential impact of this systematic risk, these foreign institutional investors have proactively incorporated climate-related factors into their decision making (Murfin and Spiegel, 2020; Choi et al., 2020; Ilhan et al., 2021; Krueger et al., 2020). Meanwhile, QFIIs may be willing to decarbonize their portfolios in order to minimize portfolios' economic losses arising from portfolio firms' exposure to cascading uncertainties induced by climate risk. In most cases,

[2] See https://www.bbc.co.uk/news/world-asia-57018837 and https://www.statista.com/statistics/239093/co2-emissions-in-china/.
[3] See https://www.bbc.co.uk/news/science-environment-54256826.
[4] See https://www.gbm.hsbc.com/insights/growth/qfiireform.

such exposure is geared towards carbon-intense firms (e.g., firms in the industries of gas, mining, transportation and construction) because these firms are more likely to encounter external pressures from regulators, business partners or clients pushing firms to align with the sustainability agenda (i.e., reducing carbon footprint). High-carbon firms may be challenged by coping with the policy uncertainties surrounding the period when carbon policies will be implemented or confronted with the transition risk driven by a shift to the low-carbon economy, leading to a higher downside risk (Ilhan et al., 2021; Hoepner et al., 2016). Thus, the financial implication of climate risk creates the first motivation for QFIIs to reduce investee firms' carbon emissions. Second, QFIIs have social incentives to drive investee firms' carbon reduction. This is because QFIIs, as fiduciary investors who work on behalf of their clients, not only consider the expected return of firms' stocks but also take into account the social norm in their decision making (Krueger et al., 2020). Since most of QFIIs come from countries with higher social awareness and sustainability commitments, they are more likely to transplant their social consciousness to firms they invest in. This in turn can strengthen their reputations and increase their investment quotas (Dyck et l., 2019; Li et al., 2020; Zhao et al., 2021; Riedl and Smeets, 2017).

Using a panel dataset of 1,977 Chinese publicly listed non-financial firms with 13,839 firm-year observations for the period 2012-2018, I find that firms with QFIIs experience a reduction in future carbon intensity, which is consistent with the main hypothesis. The size of the effect is substantial. A transition of a firm from having no QFIIs to having QFIIs produces a 51.1% (40.9% and 53.9%) reduction in firms' annual carbon emissions in the following year. This finding remains robust in a batch of robustness tests, including controlling for endogeneity and selection bias, as well as using an alternative measure of foreign shareholding.[5] To expand the understanding on the impact of QFIIs on carbon reduction, I further limit my attention on the differences in the social norm of QFIIs' home countries and find that QFIIs from countries with high social norm play a more important role in decarbonization relative to those investors from low social norm countries.[6]

I also uncover two plausible underlying economic mechanisms through which QFIIs promote decarbonization. I posit the first voting power channel by investigating whether the

[5] To mitigate concerns on endogeneity issues, I use two strategies: an instrumental variable (IV) approach and a propensity-score-matching (PSM) approach. For more details, see section 4.3, 4.4 and 6.

[6] Specifically, I employ two measures, the Environmental Performance Index (EPI) and the regulatory quality score underlying the Worldwide Governance Indicators (WGI), as proxies for the country-level norm. Then, I perform a subsample analysis based on the high and low social norm groups (split by the median of social norm measures).

effect of QFIIs' decarbonization would be stronger if QFIIs act as key shareholders.[7] The cross-sectional tests provide evidence that QFIIs as one of top ten largest shareholders with more voting power push harder for carbon reduction. Additionally, I explore the common ownership channel by comparing firms with QFIIs holding same-industry peers and firms without any QFII holding same-industry peers.[8] The result shows that the effect of QFIIs' decarbonization is greater when QFIIs concurrently hold more than one firm in the same industry of investee firms.

Lastly, I explore two regional heterogeneous effects by firms' geographic location and by QFIIs' geographic location. The evidence shows a greater effect of QFIIs' decarbonization on firms operating in inland provinces, and when QFIIs come from Asia and Australasia.

This paper contributes to the literature in at least two ways. First, it adds to a large growing body of literature on the economic outcomes of foreign institutional investors, particularly their influences on corporate governance practices. Specifically, the existing literature focuses on corporate innovation (Luong et al., 2017), long-term investment (Bena et al., 2017), corporate social responsibility (Dyck et al., 2019; Li et al.,2020; Zhao et al., 2021), global financial reporting convergence (Fang et al., 2015), earnings management (Lel, 2019), dividend policy (Baba, 2009; Kim et al., 2010; Jeon et al., 2011; Cao et al., 2017), internal control quality (Li et al., 2021), stock price crash risk (Kim et al., 2020), auditor choice (He et al., 2014), minority shareholder protection (Huang and Zhu, 2015), and stock market stability (Schuppli and Bohl, 2010). This study builds upon this literature by shedding light on a social dimension of governance that differs from those traditional governance matters: the reduction of corporate carbon emissions. Prior literature largely fails to answer the question on the effectiveness of institutional investors' engagement in decarbonization. Until recently, Azar et al. (2021), based on a sample of 7,751 publicly firms across 24 countries from 2005 to 2018, provide the first causal evidence that the Big Three are effective in reducing corporate carbon emissions, particularly for large firms with high Big Three ownership and later years in the sample period

[7] Previous literature points out institutional investors can use their "voices" to exert their influences on governance practices, particularly when they hold a large proportion of a firm's shares (Gillan and Starks, 2000; Edmans, 2009). It is plausible that the effect of QFIIs' decarbonization would be stronger if QFIIs act as key shareholders as they can have more influential impacts on firms' carbon-policy making and thus benefit more from pressuring management to cut emissions.

[8] This channel is unique and well suited to the Chinese context. It is motivated by the fact that QFIIs in China are subject to certain rules on the maximum investment holding in single stock and are thus more likely to hold multiple same-industry firms rather than having a concentrated holding on single stock when they build their portfolios based on industries. Holding multiple same-industry peers not only helps QFIIs accumulate industry-related knowledge and experience contributing to a more effective carbon-reduction process, but also increases QFIIs' incentives to monitor firms' transition to a low-carbon future due to the lower costs of information acquisition and process during decarbonization.

when the Big Three pay more attention to tackle with environmental issues. Turning to studies in China, Li et al. (2020) is the most relevant to my study, who posit a positive relationship between foreign ownership and corporate social responsibility, based on 752 Chinese listed firms with 4,145 firm-year observations from 2009 to 2017. They find that such a positive relationship is more pronounced among firms with foreign institutions from countries with high social awareness or from geographically distant countries. My work differs from theirs by looking at how all foreign investors, instead of only the Big Three, affect the carbon footprint, rather than a more general corporate social responsibility. To the best of my knowledge, this is the first study using a large panel dataset investigating the role of foreign institutions in corporate carbon reduction in China, where foreign investors have tightly restricted access to the local stock market and their involvement in environmental issues cannot be simply extrapolated from studies in western countries. The findings in this paper also imply that engagement in carbon emissions can be viewed as a positive signalling mechanism that reduces the information asymmetry arising from the geographical distance between QFIIs' home countries and investee firms' countries of origin.

More generally, this paper also complements the recent burgeoning studies on climate risk. This strand of literature provides mixed evidence on the role of climate risk in asset pricing. Much of the work documents that climate risk perceived as a long-term risk factor affects the prices of a wide range of assets, including residential real estates (Bernstein et al., 2018; Murfin and Spiegel, 2020), equities (Bolton and Kacperczyk, 2020; Bolton and Kacperczyk, 2021), options (Ilhan et al., 2021) as well as municipal bonds (Painter, 2020). Viewed broadly, people's beliefs about climate change risk are also important in the asset pricing (Baldauf et al., 2020; Chio et al., 2020). However, a few studies argue that environmental issues may only have a limited economic impact, particularly over the long-term (Hong et al., 2019; Atreya and Ferreira, 2015). Other relevant studies, like Alok et al. (2020), looking into the economic risk associated with climate risk from the perspective of behaviour finance, find that fund managers may overreact the natural disasters by underweighting those stocks recently exposed to these disasters, particularly for hurricanes and tornadoes. An irrational portfolio allocation decision-making triggered by such salience bias can be costly to fund investors. Taken together, I believe this paper is in a timely manner, given the fact that climate risk has been priced by the market (Krueger et al., 2020), and that carbon premium in China's financial market is significant (Bolton and Kacperczyk, 2020).

The remainder of the paper proceeds as follows. The next section provides background information on China's QFII scheme, discusses the related literature, and develops hypotheses.

Data sources, sample construction and research design are discussed in Section 3. Section 4 presents the summary statistics and empirical results regarding baseline regressions and motivation tests. Section 5 explores plausible underlying mechanisms. Section 6 provides results for additional tests and robustness check. Finally, section 7 concludes the paper.

2. Institutional background, literature review, and hypothesis development

2.1 Institutional background

In 2002, the QFII scheme was introduced by the China Securities Regulatory Commission (CSRC) in an attempt to open up the domestic financial markets to global investors. The general purpose of the QFII program is to manage the potential risk, induced by the large-scale speculative capital flows ("hot money") to macroeconomic and financial market instability in the process of RMB internationalization (Huang and Zhu, 2015; Li et al., 2020). The other reason for promulgating this policy is because of a widely growing concern and demand for improving corporate governance. Given the pervasive controlling shareholder entrenchment in China, compared with retail investors who dominate the stock market but lack ability to exercise their rights as minority shareholders, foreign institutional investors with professional knowledge and relatively longer investment horizons are in a better position to play a corporate governance role (Jiang and Kim, 2020; Ge et al., 2022).

Foreign investors have unique access to China's financial market. Prior to 2002, the Chinese stock markets remained isolated and foreign investors were legally prohibited from buying domestic tradeable A-shares, though they can purchase offshore shares in the form of B-, H-, and N-shares in dollars or HKD issued by only about 10% of Chinese listed companies (Huang and Zhu, 2015). While under the QFII scheme, international investors who meet certain requirements (e.g., the minimum requirement on assets under management, investment quotas, etc.,) are allowed to directly invest in the domestic A-share market.[9] At the beginning, due to stringent regulations on QFIIs' investment quota and operational ability, most foreign investors are leading investment banks, such as HSBC, Citigroup and Goldman Sachs.[10] With an ongoing development of the QFII regime, a wide range of international institutions have been attracted, including global asset management companies, insurance companies, sizable securities, endowment funds and even sovereign wealth funds, conditional on gradually relaxed entry

[9] For more detailed requirements, see https://www.safe.gov.cn/en/.

[10] In mid-2003, the UBS as the first QFII has been granted a 300 million US dollars investment quota. See www.chinadaily.com.cn/en/doc/2003-07/10/content_244331.htm.

criteria, simplified application process and expanded investment scope in recent years. Since the implementation of the QFII scheme, the QFII market has evolved rapidly in terms of both investment quota and the number of approved QFII licences.[11] As of November 2019, a total number of 292 QFIIs have received licences with a total investment quota of $111.37 billion.[12]

2.2 Literature review and hypothesis development

Institutional investors have been viewed as the most important participants in capital markets (Chemmanur et al., 2021). A large and growing body of literature has investigated institutional investors' impact on corporate practices in general, such as corporate information and trading environment (Boone and White, 2015), financial reporting (Ramalingegowda and Yu, 2012), tax planning and avoidance (Khan et al., 2017; Chen et al., 2019; Li et al., 2021), dividend policy (Crane et al., 2016), insider trading (Hillegeist and Weng, 2021; Fu et al., 2020) and corporate innovation (Aghion et al., 2013). These studies primarily focus on the role of a whole group of institutions for firms' decisions by assuming these investors' objectives and behaviours are the same. Yet in practice, institutional investors themselves are not a homogeneous group. Based on the geographic origin, institutional investors can be classified into local institutional investors and foreign institutional investors (Ferreira and Matos, 2008).

As a subset of institutional investors, foreign institutional investors have unique characteristics allowing them to better resolve common issues regarding corporate governance and ultimately to improve firm value, as highlighted by Gillan and Starks (2003).[13] First, compared with local institutional investors, foreign institutional investors are more independent and less likely to have business ties with a particular local firm, which enables them to reach a better position to monitor insiders and make appropriate investment decisions (Bena et al., 2017; Lin and Fu, 2017). Particularly in emerging economies, like China, where the government plays a predominant role in the economy, the advantage of foreign institutions over domestic institutions is salient. For instance, Huang and Zhu (2015) compares how

[11] The initial QFII quota was $4 billion in total in 2002 (with 12 QFII licenses in 2003). Then, it was increased to $10 billion in 2005, $30 billion in 2007, $80 billion in 2012, $150 billion in 2013 and $300 billion in 2019 (with 292 QFII licenses). In late 2019, the equity investment quota limits for QFIIs have been removed. See https://www.safe.gov.cn/en/.

[12] See https://www.safe.gov.cn/en/.

[13] Prior cross-country studies show that the presence of foreign institutional investors can be effective in restraining firms' earnings management activities (Lel, 2019), promoting corporate innovation (Luong et al., 2017) and driving CSR (Dyck et al., 2019). Interestingly, when turning to ESG issues, Dimson and Karakas (2015) find that foreign institutions' involvement can improve social welfare to the extent that it increases stakeholder value when engagements are successful and does not destroy firm value even when engagements are unsuccessful.

different roles played by foreign and local institutional investors are in reducing controlling shareholder expropriation. By taking advantage of a Chinese split-share reform which required investors' voting on the compensation proposals offered by non-tradable shareholders to tradable shareholders for the stock values' dilution, they find that QFIIs play a monitoring role in the negotiation process of this reform, which can be reflected on a quicker approval of the proposal and a higher compensation ratio to tradable shareholders. This is mainly because QFIIs are less subject to the political pressure from controlling state shareholders. Second, foreign institutional investors' superior performance can be attributed to their owned resources, knowledge and expertise in different areas (Huang and Shiu, 2009; Luong et al., 2017). These professional foreign investors may provide a valuable practical guidance on governance for the investee firms through their robust business networks, thus contributing to firms' long-term success.

Empirical evidence from the Chinese setting based on the panel data estimation confirms several advantages of QFIIs over local peers in improving corporate governance. Relevant studies mainly focus on information production (Li et al., 2015), minority shareholder protection (Huang and Zhu, 2015), corporate social responsibility (Li et al., 2020), earnings smoothing (Wu et al., 2015) , stock return volatility (Chen et al., 2013), internal control quality (Li et al., 2021) and stock price crash risk (Kim et al., 2020).[14] Other related studies based on the restricted sample show that opening the door to foreign investors helps mitigate the litigation risk (Xiong et al., 2021) and improve the market efficiency (Huo and Ahmed, 2017), by using the Stock Connect pilot scheme, a reform of stock market liberalization, as an exogenous shock to the variation in foreign ownership of pilot stocks. Accordingly, considering these findings in conjunction with two distinct features of foreign institutional investors discussed above, it is plausible that QFIIs' role would not be limited to governance structure, but can be expanded to the engagement in carbon reduction to some extent, given the importance of environmental issues in corporate governance matters.

Based on the discussion above, it is natural to ask why QFIIs have incentives to engage in corporate carbon reduction processes. One factor that potentially drives QFIIs to cut carbon footprint is financial motivation. That is, investee firms' exposure to carbon risk induced by the carbon emissions embedded into the climate risk may profoundly affect the value, return and

[14] Research on the effects of institutional investors (both domestic and foreign investors), particularly domestic investors in the context of China is relatively abundant. Most of studies focus on the role of domestic mutual funds and find a positive relationship between mutual fund ownership and firm performance (Yuan et al., 2008), financial reporting quality (Chan et al., 2014), dividend payouts (Firth et al., 2016) and the profitability of insider purchases (Li and Ji, 2021).

risk of portfolios. This stems from the fact that an increasing number of institutional investors, considering the importance of climate risk for firms' economic activities and financial markets, have integrated climate-related factors into their investment decision frameworks (Murfin and Spiegel, 2020; Choi et al., 2020; Ilhan et al., 2021; Krueger et al., 2020). In terms of return, empirical evidence from the perspective of asset pricing indicates that firms with good performance on sustainability are more attractive to investors, associated with higher firm values (Matsumura et al., 2013) and better long-term returns (Gibson et al., 2017; Hartzmark and Sussman, 2019).[15] Practically, an investment strategy of "long carbon-efficient firms and short carbon-inefficient firms" can bring a significant and positive abnormal return (In et al., 2019). Besides, QFIIs can also benefit from engaging in firms' carbon reduction in a way of attracting large volumes of capital from ESG-aligned investment clients (Azar et al., 2021). In terms of risk, QFIIs' effort to cut emissions of investee firms may be helpful for mitigating overall portfolios' exposure to climate and other environmental regulatory risks and thus limiting potential losses of entire portfolios. This is particularly important when QFIIs invest in Chinese firms which often face higher level of policy uncertainty compared with firms in other countries. In the case of climate policy, such uncertainty caused by the global warming may hugely affect business models, which further presents difficulties for QFIIs to predict fundamental cash flow and estimate firm value (Jagannathan et al., 2017). Compared to low-carbon firms, carbon-intense firms have higher downside risks because their profits are more sensitive to a series of carbon-reduction policies (Ilhan et al., 2021; Hoepner et al., 2016). Thus, it is reasonable that QFIIs can push firms to curb emissions because they can reap financial benefits in the form of higher financial returns and/or lower risks.

Aside from financial incentives, QFIIs may commit to reducing carbon footprint resulting from social incentives. As professional institutions, QFIIs have fiduciary duties on their clients, which requires them to take account of moral or ethical factors in their investment processes (Krueger et al., 2020). Since the economic and market environment where most of QFIIs come from has a well-designed social norm and national strategy towards the ESG issues, conformity to these rules will be subject to huge pressures from the whole society. Thus, QFIIs may be socially motivated to transplant their advanced investment philosophies and social consciousness to the firms that they invest in (Dyck et al., 2019; Li et al., 2020; Zhao et al., 2021). By pushing firms in their portfolios to cut carbon emissions, QFIIs can also build a

[15] A few studies on the effects of climate change on asset pricing have different findings. A recent study by Bolton and Kacperczyk (2021) finds a carbon premium for carbon intense firms. That is, greater emissions are associated with higher returns. This result is consistent with the evidence in Hsu et al. (2020).

positive social image and signal a good social reputation to attract inflows of funds from their potential clients who are willing to pay a premium to invest in environmentally sustainable firms (Riedl and Smeets, 2017).

Despite these findings, whether QFIIs in China have a real effect on addressing climate issues is uncertain (e.g., carbon reduction). Due to various investment preferences of QFIIs, those with short-term investment horizons may only strive for maximizing short-term spread returns, rather than waiting for a long-term payoff from tackling with environmental issues, even if such payoff is significant (Bushee, 2001). Like other Chinese domestic institutional investors, QFIIs as informed investors can also take advantage of their private information to carry on speculative trading. They gain the trading rents through frequently buying and selling stocks, but at the expense of minority shareholder interests. This is supported by Zhang et al. (2017), who document an inverted U-shape relationship between QFIIs trading turnover and tunnelling magnitude based on 1,006 firm-year observations in Chinese real estate industry. Moreover, QFIIs may lack channels to monitor their investee firms' environmental behaviours because of relatively low holding percentage in firms restricted by law.[16] In this case, these investors are inclined to remain silent even if their investee firms are associated with high potential risk to the environment, which eventually has no effect on firms' decarbonization.

In summary, motivated by Azar et al. (2021) who find that firms being a target of Big Three have lower carbon emissions, I make the following main hypothesis:

Hypothesis: Firms with the presence of QFIIs have lower corporate carbon emissions than those without QFIIs.

3. Sample selection and research design

3.1 Data sources and sample construction

The data for this paper are compiled from various sources. I obtain firm characteristics and financial information from the China Stock Market and Accounting Research (CSMAR), which is developed by GTA, one of the leading data providers in China. Data on foreign institutional ownership also come from the CSMAR database. I use the data from the National Bureau of Statistics of China to compute the provincial GDP per capita.[17] The Institutional Shareholder

[16] See https://www.law.ox.ac.uk/business-law-blog/blog/2021/07/instituional-investors-china-corporage-governance-and-policy.
[17] See https://data.stats.gov.cn/english/index.htm.

Services (ISS) database, covering about 25,000 firms around the world so far, is used to collect data on corporate carbon emissions.[18] For those non-reporting firms, according to the sector-relevant financial or operations metrics, the ISS provides the estimates of firms' annual carbon emissions based on a sophisticated method that draws on about 800 sub-sector specific models.

Corporate carbon emission data in ISS database contain the information on three kinds of emissions, capturing both direct emissions ($Scope1$) and indirect emissions ($Scope2$ and $Scope3$) that firms create in their operations and wider value chains. $Scope1$ emissions originate from sources which are owned or controlled by firms, such as emissions from combustion in owned or controlled boilers and vehicles, emissions from chemical production in owned or controlled process equipment and so on. $Scope2$ emissions occur from the generation of the electricity, steam, heating and cooling purchased and consumed by firms. $Scope3$ emissions refer to all indirect emissions not covered in $Scope2$, mainly from upstream and downstream supply chains.

Our initial sample includes the universe of Chinese public firms listed on the Main board, the SME board and the Sci-tech Innovation board of China's stock markets. I start with 18,445 firm-year observations (2,635 firms) with available data on corporate carbon emissions in ISS database for the 2012-2018 period. After merging the ISS dataset to the CSMAR database, I further eliminate a handful of firms under financial distress or any other abnormal condition (ST stock) and those at the risk of termination (*ST stock) during the entire sample period. Firms listed or delisted after 2012 (including the year 2012) are also excluded to ensure all firms in the sample have observations over the period. After restricting the sample to non-financial firms issued A shares, I have a total number of 1,977 firms with 13,839 firm-year observations from 2012 to 2018 as the final sample.

3.2 Model specification and variables definition

To examine the relation between QFIIs and corporate carbon emissions, I estimate the following model using pooled ordinary least squares (OLS) regressions:

$$Carbon\ Intensity_{i,t} = \beta_0 + \beta_1 QFII_{i,t-1} + \beta_2 FirmSize_{i,t-1} + \beta_3 Leverage_{i,t-1} + \beta_4 PPE_{i,t-1}$$

[18] Firms' carbon footprint provided by the ISS is initially drawn from all publicly available sources, such as corporate sustainability reports, the Carbon Disclosure Project (CDP) and Bloomberg surveys, and then validated through a combination of quantitative and qualitative analysis to ensure the reliability of these self-reported data. For more details, see https://www.issgovernance.com/esg/.

$$+ \beta_5 ROA_{i,t-1} + \beta_6 BM_{i,t-1} + \beta_7 Growth_{i,t-1} + \beta_8 BoardSize_{i,t-1}$$
$$+ \beta_9 FCFF_{i,t-1} + \beta_{10} SOE_{i,t-1} + \beta_{11} GDP_{i,t-1} + \beta_{12} Fixed\ Effects + \varepsilon_{i,t}$$

The dependent variable, $Carbon\ Intensity_{i,t}$, is calculated as firms' annual carbon emissions ($Scope1, 2\ and\ 3$), which is measured in equivalents of metric tons of carbon dioxide, divided by firms' total revenue (*CO_2/Revenue*), by firms' total assets (*CO_2/Assets*) and by firms' total market capitalization (*CO_2/MV*) at the end of the year, respectively. I scale firms' emissions by the end-of-year total revenue, total assets and total market capitalization because the extent to which firms emit carbon dioxide is highly correlated with firm size and market value. $QFII_{i,t-1}$ is an indicator variable that equals one for firms with at least one qualified foreign institutional investor over four quarters within the year, and zero otherwise.

Following the prior literature (Ilhan et al., 2021; Azar et al., 2021), I control for a set of firm characteristics that can affect the intensity of carbon emissions, including firm size ($FirmSize$), financial leverage ($Leverage$), capital intensity (PPE), firm profitability (ROA), book-to-market value (BM), sales growth ($Growth$), and free cash flow to the firm ($FCFF$). State ownership (SOE) is also included because a large number of major emitters (e.g., fossil fuel firms) in China are owned by the government. In addition, the inclusion of the $BoardSize$ controls for corporate governance characteristics, given that good corporate governance tends to facilitate discussions about firms' responsibilities (e.g., climate actions) to all stakeholders and thus promotes carbon performance (Luo and Tang, 2021). Considering that the regional economic development is a contributing factor to the local greenhouse effects and can further influence corporate behaviours toward carbon reduction, I also control for the GDP per capita of provinces where firms located in (GDP) in the estimation. To account for the positive time trend in corporate carbon emissions over the sample period, I include year dummies in each regression. Industry (or firm) and region fixed effects are also included in various specifications to control for the corresponding heterogeneity. I correct standard errors for firm-level clustering because I assume that observations are independent across firms. All continuous variables are winsorized at the levels of 1% and 99% to reduce the influence of outliers. Appendix B presents definitions for all variables in detail.

4. Empirical results

4.1 Descriptive statistics

Table 1 shows summary statistics for the sample of 13,839 firm-year observations from 2012 to 2018. Panel A of Table 1 reports a breakdown of sample firms across 17 CSRC industry groups.[19] Obviously, the most represented group is "Manufacturing industry (C)" which accounts for 60.85% of the sample. Apart from this sector, the sample firms are widely dispersed among the rest of the 16 industries. In addition, of all the industries in the sample, the leasing and business services industry seems to have the highest carbon intensity (2.38), followed by the wholesale and retail trade industry (0.45) as well as the real estate industry (0.37).[20] Given the essential use of fossil fuels in the industrial processes, the manufacturing industry, as another big culprit of carbon emissions with a value of 0.36 in terms of the sector's carbon intensity, also includes a large number of carbon-intensive firms. Other notable differences across industries are that QFIIs appear somewhat more prevalent in the industry of lodging and catering services (H), in which roughly 34% of the firms have QFIIs during our sample period, whereas these investors are less likely to be involved in the education industry (only 4% of the firms).[21]

Panel B of Table 1 provides descriptive statistics of main variables pertaining to the entire sample. I find that the average value of $CO2/Revnue$, $CO2/Assets$ and $CO2/MV$ is 2.77, 2.20 and 8.28, respectively. The mean value for $QFII$ is 0.17, indicating that around 17% of the sample firms have qualified foreign institutional investors during the sample period, which is similar to the prior literature (Li et al., 2020). In terms of other firm characteristics, on average, firms in the sample have a long-term debt ratio of 8%, a ratio of PPE to assets of 22%, a ROA of 4%, and a sales growth rate of 19%. Besides, 41% of the sample firms are ultimately owned by the government.

4.2 Baseline regression results

Table 2 presents estimates of the main regression model regarding the impact of QFIIs on corporate carbon emissions. Specifically, columns (1)-(3) report estimates from pooled OLS regressions where the dependent variables are three measures of corporate carbon emissions

[19] The CSRC stands for the China Securities Regulatory Commission.

[20] The measure of "carbon intensity" in Panel A of Table 1 is calculated at the industry level. Following Ilhan et al. (2021), I separately aggregate the total emissions ($Scope1, 2\ and\ 3$) and the total market capitalization of all firms within the same industry. The industry's carbon intensity is computed as the aggregated total emissions (in CO_2 equivalent CO_2e tonnes) scaled by the aggregated market capitalization (in ¥).

[21] The measure of "QFII likelihood" in Panel A of Table 1 captures the probability of QFIIs presence across industries on average, which is calculated as the mean value of the variable $QFII$ of all firms within the same industry.

over the calendar year. Controlling for year, industry and region fixed effects, I find that estimated coefficients on $QFII$ are negative and significant at the 1% level across all specifications, suggesting that the presence of QFIIs has a positive effect on limiting firms' carbon intensity. A coefficient estimate of −0.511 (−0.409 and −0.539) in model 1 (model 2 and model 3) indicates that a switch from firms without QFIIs to firms with QFIIs produces a 51.1% (40.9% and 53.9%) reduction in firms' annual carbon emissions in the following year.

Although the pooled OLS results show a negative relationship between QFIIs and corporate carbon emissions, these findings may be driven by some omitted variables that could affect both the likelihood of QFIIs entry and firms' carbon output. To address this concern, I re-estimate the main regression models with year and firm fixed effects included (with the exclusion of industry and region fixed effects that do not vary within the firm). As shown in columns (4)-(6), the results are both statistically and economically comparable to those in columns (1)-(3), which implies that our main findings are robust when controlling for time-invariant unobserved firm heterogeneity.

Turning to control variables, I find that larger firms ($FirmSize$), firms with better financial performance (ROA and $Growth$) and value firms (BM) tend to have a lower level of carbon intensity.[22] Although the coefficient signs and statistical significance of $Leverage$ and PPE are inconsistent across different model specifications, it is similar to what has been documented in the earlier work (e.g., see Azar et al., (2021) for the U.S. firms). Moreover, as expected, firms with state ownership are associated with higher carbon intensity, though the evidence is relatively weak. However, there is no clear evidence for the effect of cash flow ($FCFF$) and corporate governance ($BoardSize$) on firms' carbon intensity.

Taken together, a negative association between QFIIs and corporate carbon emissions observed in columns (1) to (6) of Table 2 highlights the role of QFIIs in driving down corporate carbon emissions, which is consistent with the main hypothesis.

4.3 Instrumental variable estimation results

So far, I provide evidence that the presence of QFIIs as shareholders is beneficial to curb corporate carbon emissions. Although my empirical analysis using lagged explanatory

[22] Since firm size is highly correlated with the independent variable ($QFII$), which affects the estimates and the magnitude of the standard errors, I orthogonalize firm size with respect to $QFII$ before running the main regression model. The way of orthogonalizing the firm size is similar to several studies on bank performance (e.g., see Beck and De Jonghe, 2016).

variables and firm fixed effects alleviates endogeneity concerns to some extent, these results may still be biased due to some omitted time-varying unobserved factors. Another concern is the reverse causality. That is, firms with lower carbon intensity might be more attractive to QFIIs in the context of the low-carbon transition, resulting in the direction of causality flows from corporate carbon emissions to QFIIs. Thus, to further support a causal interpretation of the main results, I adopt an instrumental variable (IV) approach as the first identification strategy.

Ideally, the instrument constructed in this paper should satisfy the condition that the variation in QFIIs ownership is exogenous to corporate carbon emissions. Meanwhile, such variation should not directly affect corporate carbon emissions but only through its impact on QFIIs ownership. Similar in spirit to Aggarwal et al. (2011), I use the inclusion of firms in the Stock Connect scheme as an IV for the endogenous variable $QFII$. As a milestone of the Chinese stock market openness, the Stock Connect scheme launched in 2014 aims to establish the mutual stock market access between Mainland China and Hong Kong. Following this program, foreign investors are allowed to trade in certain amounts of pilot stocks listed on the Chinese domestic stock market.[23] Given that the selection and adjustment for a pilot stock depend on whether this stock is a part of capital market indices in conjunction with the market capitalization of this stock, the variation in foreign institutional ownership induced by this rule seems to be exogenous. Additionally, I provide further support for the validity of the exclusion restriction based on the economic intuition because this condition is fundamentally untestable (Roberts and Whited, 2012). The rationale is that a firm is included in the pilot program because of its good representation as a constituent of an index, which is less likely to be directly related to the carbon output particularly after controlling for factors that determine the likelihood of being the pilot stock.[24] Thus, the $Stock\ Connect$ should be a valid instrument that meets both the relevance and exclusion criteria.

To check the relevance of the instrument, in the first stage, I use logistic regressions to

[23] Under the Stock Connect scheme, the investable securities eligible for trading by QFIIs comprise only of the constituent stocks of the SSE 180 Index and the SSE 380 Index, the constituent stocks of the SEZSE Component Index and the SZSE small/Mid Cap Innovation Index which have a market capitalization of not less than RMB six billion, and all the other SSE/SZSE-listed A shares which have corresponding H shares listed on Hong Kong Stock Exchange.

[24] There are several studies investigating the implication of the stock market liberalization by using the China's Stock Connect scheme as a quasi-natural experiment, in which one study by Zhang et al. (2021) show that firms whose stocks are eligible for trading by QFIIs have more green innovation output after the implementation of the stock market liberalization. Based on their findings, it is possible that the launch of the Stock Connect scheme helps reduce environmental pollution through increasing firms' engagement in green innovation. However, it is unclear why stock market liberalization would directly affect corporate carbon emissions, given that there is no clear evidence so far for the effect of the Stock Connect scheme on firms' carbon footprint.

estimate the likelihood of the presence of QFIIs as a function of the likelihood of being a pilot stock (IV).[25] Other explanatory variables, which are the same as those used in the baseline regression models, as well as year, industry and region fixed effects are controlled across all specifications.[26] As shown in columns (1)-(3) of Table 3, regardless of which dependent variable I use, coefficients on $Stock\ Connect$ are statistically positive at a 1% level with the p-value of the F-test of the instrument close to 0, indicating that the instrument $Stock\ Connect$ is strong and highly correlated with $QFII$.

In columns (4)-(6) of Table 3, I present the second-stage regressions using the predicted value from the first-stage regressions as the independent variable. The coefficient estimates on the fitted values of $QFII$ are negative and statistically significant at a 1% level, which suggests that a higher likelihood of QFIIs presence is associated with the subsequent decline in carbon intensity. These results remain consistent when using various dependent variables. Notably, the IV estimates yield coefficients remarkably larger than the OLS results', implying that the OLS results may underestimate the positive effects of QFIIs presence on corporate carbon emissions to a large extent.

4.4 Propensity-score-matching results

Considering the documented association between QFIIs and corporate carbon emissions may be caused by fundamental differences in firms' characteristics between firms with QFIIs and firms without QFIIs, I employ a matched sample design based on the propensity-score-matching (PSM) approach to alleviate this concern.[27] In terms of the PSM procedure, I begin the empirical analysis by obtaining the estimation for the likelihood of the presence of QFIIs (i.e., firms with QFIIs) based on the logistic regression model.[28] As shown in Appendix A, before employing the PSM, I find important differences in firm characteristics between treated observations and untreated observations. For example, the treated group includes relatively

[25] Given the fact that the Stock Connect scheme launched in 2014, the instrument data covers only the period from 2014 to 2018. For the firm-year of the instrument before 2014, I replace them with zero to ensure the sample period for all variables is consistent. Alternatively, I perform the IV analysis again for a limited sample period from 2014 to 2018. The untabulated results are similar to those exhibited in the full sample.

[26] In the IV regression, I orthogonalize firm size with respect to both $QFII$ and $Stock\ Connect$ because firm size is highly correlated with these two variables, which affects the estimates and the magnitude of the standard errors,

[27] In particular, I match each treated observation (firms with QFII ownership at the firm-year level) with an untreated observation (firms without QFII ownership at the firm-year level) that has the closest propensity scores by using the nearest neighbour matching technique (with replacement). The propensity scores are calculated using all control variables used in the baseline regressions as well as fixed effects (year, industry and region). In the PSM procedure, the way of orthogonalizing the firm size is the same as in the baseline regressions.

[28] For brevity, the estimation results from the logit regression model are untabulated but are available upon request.

large firms with stable growth rates. It is also characterized by relatively high return on assets and unlevered free cash flow. While after adopting the PSM, differences in firm attributes between two groups seems to disappear statistically, suggesting that two groups of the matched observations are similar. Besides, I demonstrate that the PSM is effectively performed in adjusting for the balance of covariates across treated and untreated observations. The balancing test results show that the mean bias drops remarkably from 8.4 percent (before PSM) to 1.6 percent (after PSM).

Table 4 presents results for the OLS (with firm-fixed effects) estimations in a matched sample. The estimates for all specifications are the same as the baseline regressions, but with a limited sample. As expected, for all three carbon intensity measures, coefficients of $QFII$ are similar to those in the main models as shown in Table 2 in terms of both economic and statistical significance.

In summary, two identification tests discussed above based on both the IV approach and PSM approach help gauge the causal effect of QFIIs presence on corporate carbon emissions, which lends relatively strong support to the main hypothesis.

4.5 Tests of the importance of social motivation

To examine the social motivation behind QFIIs' push for carbon reduction, I focus on the pressure QFIIs face from social norm of their home countries, as a society's attitudes and beliefs toward environmental issues typically have significant impacts on QFIIs' behaviours (Dyck et al., 2019). I posit that QFIIs from high social norm countries are more likely to pressure investee firms on decarbonization because of the increasing demands for environmental improvement from their own countries. To measure the social norm of QFIIs' countries, I, following Dyck et al. (2019), first use the Environmental Performance Index (EPI) representing an observed outcome of social norm, which captures a country's aggregate environmental performance.[29] I sort QFIIs into high social norm group ($QFII_High$) and low social norm group ($QFII_Low$) based on the median country rankings of EPI score for each year.[30] Since data on the EPI scores of Hong Kong and Macao is unavailable to retrieve, to avoid the biased result, firms with QFIIs from either Hong Kong or Macao are temporarily not considered as the sample of firms at this stage. Based on the results of columns (1)-(3) of Table 5, I find that

[29] For more details, see https://epi.yale.edu.

[30] High ranking group indicates the countries with better environmental performance.

the coefficients on $QFII$ are negative and significant at the 1% level across all models for both groups, compared to the group of firms without QFIIs. Further, the coefficients on $QFII$ in the high social norm group ($QFII_High$) are significantly more negative than those in the low group ($QFII_Low$) for all dependent variables. Economically, if QFIIs from low social norm economies were to push investee firms to reduce carbon emissions in the same manner as QFIIs from high social norm economies, corporate carbon intensity would decline by 8.9% (7.6% and 12.1%).[31]

For robustness, I also consider using an alternative measure to reflect QFIIs' social awareness. Since the extent to which a country's citizens abide by the rules of society is heavily affected by the country's regulatory quality, it is plausible that QFIIs from the countries with stricter environmental regulations and enforcement policies are more inclined to push harder for cutting carbon emissions, because they prefer requiring investee firms to act in accordance with high social standards as what they behave in their own countries. Following Li et al. (2020), I use the country's regulatory quality scores underlying the Worldwide Governance Indicators (WGI) obtained from the World Bank to test the prediction.[32] I split QFIIs into two groups according to the median value of countries' regulatory quality scores for each year and repeat the above subsample tests. The results, reported in columns (4)-(6) of Table 5, are similar to those exhibited in columns (1)-(3) of Table 5, although statistical and economic magnitudes here are both larger.

Overall, these results suggest that QFIIs can be socially motivated to decarbonise in a way that the negative relation between the presence of QFIIs and corporate carbon intensity is stronger for firms whose QFIIs are domiciled in the countries with high social norm, embodied as either better environmental performance or higher levels of regulatory quality.

5. Possible economic mechanisms

In this section, I explore two possible underlying economic mechanisms through which QFIIs push to reduce corporate carbon emissions. Although there are some other channels may be at play, I shed light on these two channels that any (or both) of them may contribute to the negative effect of the presence of QFIIs on firms' decarbonization.

[31] For example, in column (1), the coefficient on ($QFII_High - QFII_Low$) is −0.092. The average foreign institutional ownership for the low social norm group is 0.969 (untabulated). The economic impact of social norm is calculated as −0.092* 0.969 for $CO_2/Revenue$.

[32] High regulatory quality score group indicates the countries with high levels of regulatory quality. For more details, see info.worldbank.org/governance/wgi/.

5.1 Voting power

There are various mechanisms through which institutional investors can exert governance. Generally, prior literature documents that these professional and sophisticated investors can perform monitoring through either direct intervention in firms' operations (e.g., the so-called "voice" via shareholder proposals and proxy voting, or private engagement with management) or selling shares to exit (the so-called "voting with their feet") (Gillan and Starks, 2000; Edmans, 2009; McCahery et al., 2016). In line with this literature, it is plausible that foreign institutions through shareholder activism can influence firms' attitudes and behaviours towards carbon reduction, which can be finally reflected on the changes in the corresponding corporate policies. One important reason why these foreign institutions have such engagement incentives might be due to the large stakes they own in their portfolio firms, allowing them to benefit more from successful engagements, if any (Edmans, 2009). According to Azar et al. (2021), the Big Three's engagement in carbon reduction is stronger among portfolio firms with more shares held by the Big Three, implicitly in conjunction with more voting power. Thus, following this logic stream, it is natural to posit that the effectiveness of QFIIs' decarbonization is supposed to be greater when QFIIs have larger shareholdings in their portfolio firms because they are entitled to "voice" in public attributed to their voting power.

To test the voting power mechanism, one would ideally use a dataset that are available to observe QFIIs' voting behaviour as the confirmation of QFIIs' use of this instrument. Unfortunately, such dataset does not exist as the voting process of specific shareholder proposals is unobservable for Chinese publicly listed firms. Motivated by Li et al. (2020) and Li et al. (2021), I instead consider an indirect way of measurement based on the position of QFIIs as shareholders in the firm, depending on the proportion of ownership held by QFIIs, to represent QFIIs' influence and voting power on a particular firm. Specifically, I split the full sample into two according to whether firms have QFIIs as one of the top ten largest shareholders ($QFII_Top10$ and $QFII_NonTop10$) and expect a stronger result for the group of $QFII_Top10$. I present the results in columns (1)-(3) of Table 6. I rerun the baseline regression models but focus attention on the differences in the coefficients on $QFII_Top10$ and $QFII_NonTop10$.[33] Consistent with the expectation, the coefficient estimates on $QFII_Top10$ and $QFII_NonTop10$ are both negative and significant at the 1% level in all columns, while

[33] Specifically, $QFII_Top10$ is an indicator that takes the value of one for firms with at least one QFII as one of the top ten largest shareholders in a calendar year, and zero otherwise. Similarly, $QFII_NonTop10$ is an indicator that takes the value of one for firms with QFIIs but without any QFII as one of the top ten largest shareholders in a calendar year, and zero otherwise. Firms without QFIIs are always assigned to zero.

the magnitudes of this negative relation are significantly larger when QFIIs become one of the top ten largest shareholders. This provides support for the voting power mechanism as more active engagement of QFIIs in corporate carbon reduction would be expected if QFIIs increase their holding stakes of firms they invest in.

5.2 Common ownership

In addition to the voting power mechanism, foreign institutional investors may also facilitate corporate carbon reduction through common institutional ownership, that is, holding multiple firms in the same industry of investee firms in their portfolios. This mechanism is unique in the Chinese context as QFIIs in China typically face significant investment barriers legally in terms of the percentage of eligible equity holdings in single firm, which makes difficult to explicitly clarify the role of these intervened investors play in governance practices.[34] The burgeoning literature on cross-ownership documents various outcomes of institutions' holdings in peer firms, mainly with respect to product market competition (He and Huang, 2017; Koch et al., 2021), internalizing corporate governance externalities (He et al., 2019) and financial reporting (Ramalingegowda et al., 2021). Compared with QFIIs holding smaller stakes across numerous unrelated firms, QFIIs holding more same-industry peers have at least two advantages. For one, firms in the same industry tend to have similar business activities, operating environments, product scopes and even customer bases. This makes the generalization of similar decarbonization patterns across peer firms possible because the sources and even the amount of carbon emissions emitted for these same-industry peers may be similar as well. Through simultaneously holding multiple firms within the same industry, QFIIs are able to gain some knowledge and experiences related to a specific industry that can be used to make investment decision-making not only for the investee firm itself but also for other focal firms, thus resulting in the aggregate carbon reduction more effective. Besides, it is asserted that common ownership is helpful for improving monitoring efficiency due to the economy of scale mechanism (Ramalingegowda et al., 2021). In other words, the common features among the same-industry peers mentioned above are likely to incur lower costs of information acquisition and process during decarbonization that can increase QFIIs' incentives to monitor firms' transition to a low-carbon future. Based on these discussions, I thus postulate that QFIIs with common ownership, compared to those without common ownership, can better push investee firms' decarbonization.

[34] For more detailed requirements, see https://www.safe.gov.cn/en/.

To test this prediction, I partition firms into two subsamples according to whether firms have QFIIs holding multiple same-industry peers of investee firms. In terms of the measure of common ownership, following He and Huang (2017), I generate a dummy variable that equals one for firms with at least one QFII concurrently holding more than one firm in the same industry of investee firms in any of the four quarters in a calendar year, and zero otherwise. I use 17 categories of industries (except financial industry) based on the CSRC industry classification to identify peer firms. The corresponding results are reported in columns (4)-(6) of Table 6. Again, I reestimate the main regressions with the same controls as in Table 2 but replace $QFII$ with $QFII_Common$ and $QFII_NonCommon$t. In all models, the coefficients on $QFII_Common$ and $QFII_NonCommon$ are negative and significant at the 1% level, while in two out of three models, the magnitudes of this negative relation are significantly larger among QFIIs with common ownership. The findings provide evidence generally consistent with QFIIs reducing firms' carbon intensity through common ownership.

6. Additional tests and results

In this section, I perform two sets of supplemental tests as well as a robustness test for the main results reported in Table 2. First, I examine regional heterogeneity in the relation between the presence of QFIIs and corporate carbon emissions by comparing the differences in the effect of QFIIs' decarbonization between firms operate in provinces with high air pollution and low air pollution, given that carbon emissions and air quality are closely related. I hypothesis that QFIIs as the market-based mechanism are expected to be more important for areas where air quality is relatively low normally as a result of inappropriate policy interventions relating to environmental management. I distinguish high air-polluted regions with low air-polluted regions according to firms' geographical location and run a subsample analysis based on whether firms operate in coastal provinces or not.[35] This is due to coastal areas are often exposed to consistent coastal breezes enabling to disperse air pollutant to a large extent, provinces in coastal zones generally have better air quality, compared to inland provinces. Panel A of Table 7 reports the results of estimating the relation between $QFII$ and various carbon intensity variables for the coastal group and inland group separately. The evidence shows that across all models, the coefficients on $QFII$ are negative and significant at the 1%

[35] Following Jiang et al. (2014), I define a firm as "coastal" if the firm operate in one of the eleven coastal provinces, which are Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Guangxi, Hainan, Tianjin, and Shanghai.

level for both groups, while the magnitudes of the negative coefficients on $QFII$ are larger for the inland group. The difference in the coefficient between the coastal group and inland group is statistically significant at the 10% level (with the exception of Models 3 and 4). These findings suggest that the marginal effect of QFIIs' decarbonization is stronger when firms operate in the inland provinces which are more likely to suffer severe air pollution.

Next, I turn to look at the second set of regional heterogeneity by exploring whether the main results are driven by QFIIs' geographic location. To analyse the impact differentials within different areas QFIIs located in, I group QFIIs by three geographic regions: Europe, Americas, as well as Asia and Australasia according to QFIIs' home countries, and then repeat the main regressions respectively. As can be seen from Panel B of Table 7, for all measures of carbon intensity, the estimates indicate that firms with QFIIs domiciled in either the Europe, Americas, or Asia and Australasia are associated with lower carbon intensity relative to firms without QFIIs in a given year. More importantly, among three groups of QFIIs, Asian and Australian investors push firms' carbon reduction more, as the coefficients on $QFII$ from Asia and Australasia group are significantly larger than the corresponding ones for other two groups. These results imply that geographical distance between QFIIs' home countries and target firms' countries does matter through which QFIIs from near-distance countries (i.e., Asian) tend to exert more influences on firms' decarbonization possibly due to less information asymmetry they face.

The final set of test examines the robustness of the main results to an alternative measure of $QFII$. I replace the $QFII$ dummy with a continuous variable, defined as the fraction of a firm's shares owned by QFIIs, to capture the magnitude of foreign shareholding. Panel C of Table 7 replicates the baseline models from Table 2, with the same control variables as in the baseline test. I observe patterns similar to those in the main regression models (Table 2), although the magnitudes and statistical significance here for the coefficients on QFII ownership are relatively smaller and lower. In general, the evidence in Table 7 confirms that the main results are not sensitive to an alternative measure of $QFII$.

7. Conclusion

In this paper, I explore the impact of foreign institutional investors on corporate carbon reduction. Using a large sample of Chinese publicly listed firms from 2012 to 2018, I find that firms with QFIIs are associated with a subsequent decline in carbon intensity measured as three

proxies. To address endogeneity issues, I use both an IV approach and an PSM approach to ensure the main results are causal. I further explore two motivations behind QFIIs' push for carbon reduction. Apart from the financial motivation, I also find evidence supporting the social motivation, that is, QFIIs domiciled in high social norm countries play a more significant role in cutting carbon footprint. Then, I pin down two mechanisms through which QFIIs' engagement in firms' carbon reduction can be realized, which are voting power and common ownership. Specifically, I find the negative relation between the presence of QFIIs and carbon intensity reduction is stronger among firms with QFIIs as one of the top ten largest shareholders and among firms with QFIIs holding same-industry peers of investee firms. Cross-sectional tests also show that the effect of QFIIs' decarbonization is stronger when firms operate in the inland provinces where air pollution is severe and when QFIIs come from Asia and Australasia with shorter physical distances to China.

Collectively, this article has empirical and policy implications both. It highlights the importance of introducing foreign institutional investors in tackling with climate issues, particularly carbon reduction. In addition, it expands the understanding on why and how these sophisticated investors are willing to engage with firms on environmental issues. Lastly, this study may also be helpful for policy makers in other emerging markets where engagement efforts to cut carbon emissions have been prioritized.

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Appendix A. Procedure to construct the propensity-score-matched (PSM) sample

The propensity-score-matching (PSM) technique aims to pair treated units and control units to make two groups more alike conditional on certain observable characteristics (Dehejia and Wahba, 2002). The first step in this procedure is to obtain the estimation for the likelihood of the presence of QFIIs (i.e., firms with QFIIs) by running a logistic regression model based on the entire sample of firms. Next, I use the predicted probability from the first step to estimate the propensity score of each firm-year. Then, I match each treated observation with an untreated (control) observation using the nearest neighbour matching technique with replacement. Panel A shows the estimation results from the logit regression model. Panel B reports the effectiveness of PSM approach. All variables are defined in Appendix B. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 level, respectively.

Panel A: Results of the logit regression

Variables	Dependent variable = Presence of QFIIs Coefficient	Z-stat.
$FirmSize$ (orthogonalized)	0.127***	5.71
$Leverage$	−1.353***	−5.94
PPE	0.851***	6.62
ROA	7.222***	15.48
BM	0.221***	4.02
$Growth$	−0.138***	−3.20
$BoardSize$	0.243**	2.47
$FCFF$	−0.117	−1.03
SOE	0.432***	10.40
GDP	0.236***	5.01

Panel B: Descriptive statistics of treated and untreated observations before and after matching

Variables		Mean value, treated firms (1)	Mean value, control firms (2)	% Bias	Diff. (1)−(2)
$FirmSize$ (orthogonalized)	Pre-match	0.194	−0.079	21.7	0.273***
	Post-match	0.192	0.183	0.7	0.009
$Leverage$	Pre-match	0.077	0.076	1.1	0.001
	Post-match	0.077	0.078	−1.0	−0.001
PPE	Pre-match	0.234	0.211	13.7	0.023***
	Post-match	0.234	0.237	−2.1	−0.004
ROA	Pre-match	0.044	0.032	25.5	0.012***
	Post-match	0.044	0.043	0.5	0.000
BM	Pre-match	−0.568	−0.626	12.0	0.058***
	Post-match	−0.568	−0.581	2.7	0.013
$Growth$	Pre-match	0.182	0.199	−3.7	−0.017*
	Post-match	0.182	0.178	0.8	0.004
$BoardSize$	Pre-match	2.167	2.136	15.6	0.031***
	Post-match	2.167	2.168	−0.6	−0.001
$FCFF$	Pre-match	0.037	0.021	9.1	0.016***
	Post-match	0.037	0.038	−0.4	−0.001

Table Continued Overleaf

Table 4 (Continued)

Panel B: Descriptive statistics of treated and untreated observations before and after matching					
Variables		Mean value, treated firms (1)	Mean value, control firms (2)	% Bias	Diff. (1)−(2)
SOE	Pre-match	0.481	0.361	24.4	0.120***
	Post-match	0.480	0.486	−1.3	−0.006
GDP	Pre-match	10.990	10.948	9.8	0.042***
	Post-match	10.990	10.995	−1.3	-0.005

Appendix B. Variable Definitions

This table provides definitions for the key variables used in the analysis.

Variable	Definition
BM	Natural logarithm of the book-to-market ratio, which is calculated as the book value of assets scaled by the market value of assets. Market value of assets is book value of total assets minus book value of equity plus market value of equity.
BoardSize	Natural logarithm of the number of directors on the board.
CO2/Assets	Natural logarithm of *CO2/Assets.* Corporate carbon intensity (*CO2/Assets*) is computed as firms' annual total carbon emissions (metric tons of CO_2) divided by firms' total assets at the end of the year. Firms' annual carbon emissions include *Scope1, Scope2 and Scope3* emissions.
CO2/MV	Natural logarithm of *CO2/MV.* Corporate carbon intensity (*CO2/MV*) is computed as firms' annual total carbon emissions (metric tons of CO_2) divided by firms' total market capitalization at the end of the year. Firms' annual carbon emissions include *Scope1, Scope2 and Scope3* emissions.
CO2/Revenue	Natural logarithm of *CO2/Revenue.* Corporate carbon intensity (*CO2/Revenue*) is computed as firms' annual total carbon emissions (metric tons of CO_2) divided by firms' total revenue at the end of the year. Firms' annual carbon emissions include *Scope1, Scope2 and Scope3* emissions.
FCFF	Free cash flow to firms divided by total assets.
FirmSize	Natural logarithm of total assets.
GDP	Provincial GDP per capita.
Growth	Annual sales growth rate, calculated as sales in year t minus sales in year t-1, divided by sales in year t-1.
Leverage	Long-term debt divided by total assets.
PPE	Fixed assets, calculated as property, plant and equity divided by total assets.
QFII	Indicator variable that equals one for firms with at least one qualified foreign institutional investor over four quarters within the year.
ROA	Return on assets, calculated as net income divided by total assets.
SOE	Indicator variable that equals one if the firm is ultimately controlled by the government, zero otherwise.

Table 1
Descriptive statistics

This table presents summary statistics for the observations and main variables used in the empirical estimations over the period of 2012-2018. The sample consists of 1,977 A-share non-financial firms (with 13,839 firm-year observations) publicly listed on the Main board, the SME board and the Sci-tech Innovation board of China's stock markets. Panel A reports the distribution of the sample firms by industries based on the CSRC (China Securities Regulatory Commission) classification. Panel B reports the number of observations, mean, standard deviation, 25th percentile, median and 75th percentile for each variable. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. All variables are defined in Appendix B.

Panel A: Sample distribution by industry group

Industry	CSRC Code	No. of obs.	No. of firms	Fraction (%)	Carbon intensity	QFII likelihood
Farming, forestry, animal husbandry and fishery	A	168	24	1.21	0.08	0.17
Mining industry	B	364	52	2.63	0.01	0.18
Manufacturing industry	C	8,421	1,203	60.85	0.36	0.17
Production and supply of electric power, gas and water	D	539	77	3.89	0.06	0.15
Construction industry	E	350	50	2.53	0.07	0.22
Wholesale and retail trade	F	847	121	6.12	0.45	0.17
Transport, storage and post	G	497	71	3.59	0.08	0.24
Lodging and catering services	H	56	8	0.40	0.03	0.34
Information transmission, computer services and software	I	994	142	7.18	0.04	0.14
Real estate	K	742	106	5.36	0.37	0.14
Leasing and business services	L	217	31	1.57	2.38	0.15
Scientific research and technical service	M	56	8	0.40	0.02	0.11
Water conservancy, environment and public facilities management	N	217	31	1.57	0.15	0.20
Education	P	28	4	0.20	0.00	0.04
Health and social work	Q	63	9	0.46	0.05	0.14
Culture, sports and entertainment	R	182	26	1.32	0.04	0.20
Conglomerates	S	98	14	0.71	0.32	0.08
Total		13,839	1,977	100		

Table 1 (Continued)

Panel B: Descriptive statistics of main variables

Variables	No. of obs.	Mean	SD	P25	Median	P75
$CO2/Revenue$	12,231	2.77	2.14	1.12	2.34	3.90
$CO2/Assets$	12,232	2.20	1.91	0.73	1.71	3.13
$CO2/MV$	12,219	8.28	2.34	6.77	8.05	9.58
$QFII$	13,839	0.17	0.37	0.00	0.00	0.00
$FirmSize$	13,839	22.20	1.28	21.29	22.04	22.95
$Leverage$	13,351	0.08	0.10	0.00	0.03	0.12
PPE	13,839	0.22	0.17	0.09	0.18	0.31
ROA	13,839	0.04	0.05	0.01	0.03	0.06
BM	13,360	−0.60	0.48	−0.87	−0.49	−0.23
$Growth$	13,621	0.19	0.45	−0.02	0.11	0.27
$BoardSize$	13,823	2.15	0.20	2.08	2.20	2.20
$FCFF$	13,624	0.03	0.18	−0.03	0.06	0.13
SOE	13,832	0.41	0.49	0.00	0.00	1.00
GDP	13,839	10.97	0.44	10.61	10.99	11.32

Table 2
Baseline regressions

This table displays the regression results for the impact of qualified foreign institutional investors on corporate carbon emissions based on a sample of 1,977 firms over the 2012-2018 period. The columns (1)-(3) present the pooled ordinary least squares (OLS) regression estimates, while the columns (4)-(6) present the firm fixed effects regression results. The first dependent variable ($CO2/Revenue$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total revenue at the end of the year. The second dependent variable ($CO2/Assets$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total assets at the end of the year. The third dependent variable ($CO2/MV$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' market capitalization at the end of the year. The main independent variable ($QFII$) is an indicator variable that equals one for firms with at least one qualified foreign institutional investor over four quarters within the year. Columns (1)-(3) control for year, industry and region fixed effects, while columns (4)-(6) control for year and firm fixed effects. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$QFII$	**−0.511*****	**−0.409*****	**−0.539*****	**−0.510*****	**−0.413*****	**−0.549*****
	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)
$FirmSize$	**−0.721*****	**−0.580*****	**−0.717*****	**−0.723*****	**−0.587*****	**−0.727*****
(orthogonalized)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)
$Leverage$	**1.719*****	**−0.063**	**0.886***	**1.018****	**−0.137**	**0.825**
	(0.42)	(0.36)	(0.50)	(0.46)	(0.40)	(0.54)
PPE	**−0.599****	**−0.119**	**−0.411**	**−0.734*****	**−0.084**	**−0.252**
	(0.26)	(0.23)	(0.30)	(0.28)	(0.25)	(0.32)
ROA	**−3.153*****	**−2.033*****	**−3.690*****	**−3.496*****	**−2.070*****	**−3.698*****
	(0.82)	(0.74)	(0.90)	(0.82)	(0.74)	(0.90)
BM	**−0.213****	**−0.176***	**0.859*****	**−0.252****	**−0.208****	**0.792*****
	(0.10)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)
$Growth$	**−0.122****	**−0.029**	**−0.062**	**−0.119****	**−0.026**	**−0.053**
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
$BoardSize$	**0.229**	**0.210**	**0.308**	**0.215**	**0.220**	**0.345**
	(0.19)	(0.17)	(0.22)	(0.19)	(0.16)	(0.22)
$FCFF$	**−0.059**	**−0.006**	**0.123**	**−0.103**	**−0.022**	**0.104**
	(0.12)	(0.11)	(0.14)	(0.12)	(0.11)	(0.14)

Table Continued Overleaf

Table 2 (Continued)

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
SOE	**0.086**	**0.182****	**0.367*****	**0.067**	**0.171***	**0.358*****
	(0.10)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)
GDP	**−0.151**	**−0.082**	**−0.236****	**−0.152**	**−0.066**	**−0.240****
	(0.11)	(0.09)	(0.12)	(0.10)	(0.09)	(0.12)
Constant	**3.694*****	**2.613****	**10.805*****	**3.973*****	**2.372****	**10.691*****
	(1.22)	(1.09)	(1.39)	(1.19)	(1.08)	(1.37)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO
Region FE	YES	YES	YES	NO	NO	NO
No. of obs.	11,162	11,163	11,161	11,162	11,163	11,161
R-squared	0.184	0.161	0.110	0.192	0.165	0.116

Table 3
Instrumental variable approach

This table reports the two-stage least squares (2SLS) regressions of corporate carbon emissions on qualified foreign institutional investors based on a sample of 1,977 firms over the 2012-2018 period. The first dependent variable ($CO2/Revenue$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total revenue at the end of the year. The second dependent variable ($CO2/Assets$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total assets at the end of the year. The third dependent variable ($CO2/MV$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' market capitalization at the end of the year. The main independent variable ($QFII$) is instrumented with $Stock\ Connect$ (a dummy variable that equals one if the firm is eligible for trading under either the Shanghai-Hong Kong Stock Connect scheme or the Shenzhen-Hong Kong Stock Connect scheme in a given year, and zero otherwise). All models include year, industry and region fixed effects. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

	1SLS			2SLS		
	$QFII_Revenue$	$QFII_Assets$	$QFII_MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$Stock\ Connect$	**0.208*****	**0.208*****	**0.208*****			
	(0.07)	(0.07)	(0.07)			
$QFII$				**−4.075*****	**−3.277*****	**−4.351*****
				(0.27)	(0.24)	(0.30)
$FirmSize$ (orthogonalized)	**−0.280*****	**−0.280*****	**−0.280*****	**−1.850*****	**−1.488*****	**−1.914*****
	(0.03)	(0.03)	(0.03)	(0.08)	(0.07)	(0.09)
$Leverage$	**0.274**	**0.274**	**0.274**	**2.824*****	**0.825*****	**2.058*****
	(0.30)	(0.30)	(0.30)	(0.25)	(0.23)	(0.29)
PPE	**0.369****	**0.369****	**0.369****	**0.882*****	**1.072*****	**1.167*****
	(0.16)	(0.16)	(0.16)	(0.15)	(0.14)	(0.18)
ROA	**11.034*****	**11.034*****	**11.034*****	**41.200*****	**33.630*****	**43.715*****
	(0.66)	(0.66)	(0.66)	(3.04)	(2.75)	(3.48)
BM	**0.826*****	**0.826*****	**0.826*****	**3.116*****	**2.501*****	**4.409*****
	(0.08)	(0.08)	(0.08)	(0.24)	(0.21)	(0.27)
$Growth$	**−0.083**	**−0.083**	**−0.083**	**−0.455*****	**−0.297*****	**−0.421*****
	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.06)
$BoardSize$	**0.223***	**0.223***	**0.223***	**1.126*****	**0.932*****	**1.269*****
	(0.13)	(0.13)	(0.13)	(0.12)	(0.11)	(0.14)

Table Continued Overleaf

Table 3 (Continued)

	1SLS			2SLS		
	$QFII_Revenue$	$QFII_Assets$	$QFII_MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$FCFF$	**0.076**	**0.076**	**0.076**	**0.239****	**0.234****	**0.441*****
	(0.15)	(0.15)	(0.15)	(0.12)	(0.10)	(0.13)
SOE	**0.673*****	**0.673*****	**0.673*****	**2.787*****	**2.354*****	**3.250*****
	(0.05)	(0.05)	(0.05)	(0.19)	(0.17)	(0.21)
GDP	**0.299*****	**0.299*****	**0.299*****	**1.049*****	**0.883*****	**1.047*****
	(0.06)	(0.06)	(0.06)	(0.10)	(0.09)	(0.11)
Constant	**−5.922*****	**−5.922*****	**−5.922*****	**−20.037*****	**−16.467*****	**−14.582*****
	(0.75)	(0.75)	(0.75)	(1.73)	(1.56)	(1.98)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
F-test	**144.49**	**115.78**	**127.73**			
(p-value)	(0.00)	(0.00)	(0.00)			
No. of obs.	12,672	12,672	12,672	11,162	11,163	11,161
Pseudo/ R-squared	0.057	0.057	0.057	0.178	0.157	0.105

Table 4
Propensity-score-matching approach

This table repeats the analysis in Table 2 using a reduced sample of firms with 2,907 observations in the treated group and 2,927 observations in the control group from 2012 to 2018 and reports the post-match results for OLS estimations in columns (1)-(3) and firm-fixed effects regressions in columns (4)-(6). The first dependent variable ($CO2/Revenue$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total revenue at the end of the year. The second dependent variable ($CO2/Assets$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total assets at the end of the year. The third dependent variable ($CO2/MV$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' market capitalization at the end of the year. The main independent variable ($QFII$) is an indicator variable that equals one for firms with at least one qualified foreign institutional investor over four quarters within the year. Columns (1)-(3) control for year, industry and region fixed effects, while columns (4)-(6) control for year and firm fixed effects. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$QFII$	**−0.551*****	**−0.443*****	**−0.513*****	**−0.543*****	**−0.449*****	**−0.525*****
	(0.08)	(0.08)	(0.10)	(0.08)	(0.08)	(0.10)
$FirmSize$	**−0.711*****	**−0.574*****	**−0.664*****	**−0.715*****	**−0.581*****	**−0.677*****
(orthogonalized)	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)	(0.06)
$Leverage$	**1.569*****	**−0.092**	**0.777**	**0.936***	**−0.122**	**0.775**
	(0.47)	(0.40)	(0.56)	(0.53)	(0.45)	(0.62)
PPE	**−0.707****	**−0.199**	**−0.362**	**−0.789****	**−0.157**	**−0.182**
	(0.29)	(0.26)	(0.34)	(0.32)	(0.28)	(0.36)
ROA	**−3.656*****	**−2.374*****	**−3.971*****	**−3.831*****	**−2.351*****	**−3.863*****
	(0.92)	(0.83)	(0.99)	(0.92)	(0.83)	(0.98)
BM	**−0.208***	**−0.170**	**0.794*****	**−0.222***	**−0.181***	**0.754*****
	(0.12)	(0.10)	(0.12)	(0.12)	(0.11)	(0.13)
$Growth$	**−0.129****	**−0.026**	**−0.037**	**−0.126****	**−0.023**	**−0.024**
	(0.06)	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)
$BoardSize$	**0.129**	**0.143**	**0.265**	**0.116**	**0.161**	**0.312**
	(0.22)	(0.19)	(0.25)	(0.22)	(0.19)	(0.25)
$FCFF$	**−0.134**	**−0.066**	**0.096**	**−0.173**	**−0.078**	**0.080**
	(0.17)	(0.16)	(0.19)	(0.17)	(0.16)	(0.19)

Table Continued Overleaf

Table 4 (Continued)

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
SOE	**0.064**	**0.176***	**0.358*****	**0.054**	**0.172***	**0.352*****
	(0.11)	(0.10)	(0.12)	(0.11)	(0.10)	(0.13)
GDP	**−0.192**	**−0.109**	**−0.241***	**−0.192**	**−0.091**	**−0.225***
	(0.13)	(0.11)	(0.14)	(0.12)	(0.11)	(0.14)
Constant	**4.418*****	**3.094****	**10.990*****	**4.663*****	**2.801****	**10.596*****
	(1.46)	(1.32)	(1.63)	(1.42)	(1.29)	(1.59)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO
Region FE	YES	YES	YES	NO	NO	NO
No. of obs.	5,793	5,793	5,793	5,793	5,793	5,793
R-squared	0.170	0.151	0.097	0.178	0.154	0.103

Table 5
QFIIs' social norm and corporate carbon emissions

This table presents the regression estimates for the relation between the presence of qualified foreign institutional investors grouped by social norm of foreign institutional investors' home countries and corporate carbon emissions over the 2012-2018 period. The analyses in columns (1)-(3) are based on a restricted sample that excludes firms with QFIIs domiciled in either Hong Kong or Macao, whereas the analyses in columns (4)-(6) are based on the full sample. The social norm of QFIIs' home countries is measured using the rankings of Environmental Performance Index (EPI) in columns (1)-(3) and the regulatory quality scores underlying the Worldwide Governance Indicators (WGI) in columns (4)-(6), respectively. The main independent variable $QFII$ is sorted into high social norm group ($QFII_High$) and low social norm group ($QFII_Low$) either based on the median country rankings of EPI score for each year (Models 1-3) or based on the median value of countries' regulatory quality scores for each year (Models 4-6). Either $QFII_Low$ or $QFII_High$ is set to zero if a stock is not held by any QFII. The first dependent variable ($CO2/Revenue$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total revenue at the end of the year. The second dependent variable ($CO2/Assets$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total assets at the end of the year. The third dependent variable ($CO2/MV$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' market capitalization at the end of the year. All models control for year, industry and region fixed effects. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

	Environmental Performance Index (EPI)			Regulatory Quality Score (RQS)		
	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$QFII_High$	**−0.457*****	**−0.366*****	**−0.465*****	**−0.627*****	**−0.481*****	**−0.636*****
	(0.10)	(0.09)	(0.12)	(0.09)	(0.09)	(0.11)
$QFII_Low$	**−0.365*****	**−0.288*****	**−0.340*****	**−0.370*****	**−0.321*****	**−0.421*****
	(0.11)	(0.10)	(0.13)	(0.08)	(0.08)	(0.10)
$FirmSize$	**−0.728*****	**−0.589*****	**−0.671*****	**−0.721*****	**−0.581*****	**−0.718*****
(orthogonalized)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)	(0.05)
$Leverage$	**1.910*****	**0.099**	**0.779**	**1.720*****	**−0.061**	**0.888***
	(0.46)	(0.39)	(0.54)	(0.42)	(0.36)	(0.50)
PPE	**−0.911*****	**−0.370**	**−0.569***	**−0.598****	**−0.118**	**−0.410**
	(0.29)	(0.25)	(0.33)	(0.26)	(0.23)	(0.30)
ROA	**−3.163*****	**−2.065****	**−3.767*****	**−3.153*****	**−2.034*****	**−3.691*****
	(0.89)	(0.81)	(0.96)	(0.82)	(0.74)	(0.90)
BM	**−0.231****	**−0.188***	**0.781*****	**−0.212****	**−0.174***	**0.860*****
	(0.11)	(0.10)	(0.12)	(0.10)	(0.09)	(0.11)

Table Continued Overleaf

Table 5 (Continued)

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$Growth$	**−0.145*****	**−0.044**	**−0.089**	**−0.122****	**−0.029**	**−0.061**
	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.05)
$BoardSize$	**0.329**	**0.305***	**0.449***	**0.229**	**0.211**	**0.309**
	(0.21)	(0.18)	(0.24)	(0.19)	(0.17)	(0.22)
$FCFF$	**−0.040**	**0.022**	**0.189**	**−0.059**	**−0.007**	**0.121**
	(0.13)	(0.12)	(0.15)	(0.12)	(0.11)	(0.14)
SOE	**0.073**	**0.168***	**0.363*****	**0.086**	**0.182****	**0.366*****
	(0.10)	(0.10)	(0.12)	(0.10)	(0.09)	(0.11)
GDP	**−0.161**	**−0.077**	**−0.183**	**−0.151**	**−0.083**	**−0.237****
	(0.12)	(0.11)	(0.13)	(0.11)	(0.09)	(0.12)
Constant	**3.799*****	**2.538****	**10.164*****	**3.697*****	**2.622****	**10.813*****
	(1.35)	(1.21)	(1.52)	(1.22)	(1.09)	(1.39)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
No. of obs.	9,635	9,636	9,634	11,162	11,163	11,161
R-squared	0.163	0.144	0.092	0.184	0.161	0.110

Table 6
Economic mechanisms: Voting power and common ownership

This table reports the results on how voting power channel (Models 1-3) and common ownership channel (Models 4-6) separately explain the effect of QFIIs' presence on corporate carbon emissions based on a sample of 1,977 firms over the 2012-2018 period. In columns (1)-(3), $QFII_Top10$ is an indicator that takes the value of one for firms with at least one QFII as one of the top ten largest shareholders in a calendar year, and zero otherwise, whereas $QFII_NonTop10$ is an indicator that takes the value of one for firms with QFIIs but without any QFII as one of the top ten largest shareholders in a calendar year, and zero otherwise. Either $QFII_Top10$ or $QFII_NonTop10$ is set to zero if a stock is not held by any QFII. In columns (4)-(6), $QFII_Common$ is an indicator that equals one for firms with at least one QFII concurrently holding more than one firm in the same industry of investee firms in any of the four quarters in a calendar year, and zero otherwise, while $QFII_NonCommon$ is an indicator that equals one for firms with QFIIs but without any QFII concurrently holding more than one firm in the same industry of investee firms in any of the four quarters in a calendar year, and zero otherwise. Either $QFII_Common$ or $QFII_NonCommon$ is set to zero if a stock is not held by any QFII. Peer firms are identified based on 17 categories of CSRC industry classification (except financial industry). The first dependent variable ($CO2/Revenue$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total revenue at the end of the year. The second dependent variable ($CO2/Assets$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total assets at the end of the year. The third dependent variable ($CO2/MV$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' market capitalization at the end of the year. All models control for year, industry and region fixed effects. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

	Voting power			Common ownership		
	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$QFII_Top10$	**−0.556*****	**−0.427*****	**−0.561*****			
	(0.09)	(0.08)	(0.12)			
$QFII_NonTop10$	**−0.377*****	**−0.357*****	**−0.477*****			
	(0.08)	(0.07)	(0.10)			
$QFII_Common$				**−0.507*****	**−0.415*****	**−0.551*****
				(0.07)	(0.07)	(0.09)
$QFII_NonCommon$				**−0.520*****	**−0.394*****	**−0.508*****
				(0.13)	(0.12)	(0.15)
$FirmSize$ (orthogonalized)	**−0.724*****	**−0.584*****	**−0.722*****	**−0.720*****	**−0.579*****	**−0.716*****
	(0.04)	(0.03)	(0.05)	(0.04)	(0.03)	(0.05)

Table Continued Overleaf

Table 6 (Continued)

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$Leverage$	**1.736*****	**−0.045**	**0.908***	**1.709*****	**−0.074**	**0.871***
	(0.42)	(0.36)	(0.50)	(0.42)	(0.36)	(0.50)
PPE	**−0.611****	**−0.133**	**−0.428**	**−0.599****	**−0.119**	**−0.411**
	(0.26)	(0.23)	(0.30)	(0.26)	(0.23)	(0.30)
ROA	**−3.149*****	**−2.029*****	**−3.685*****	**−3.142*****	**−2.021*****	**−3.674*****
	(0.82)	(0.74)	(0.90)	(0.82)	(0.74)	(0.90)
BM	**−0.208****	**−0.170***	**0.866*****	**−0.214****	**−0.177***	**0.857*****
	(0.10)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)
$Growth$	**−0.119****	**−0.027**	**−0.059**	**−0.123****	**−0.030**	**−0.063**
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
$BoardSize$	**0.234**	**0.216**	**0.314**	**0.229**	**0.210**	**0.307**
	(0.19)	(0.17)	(0.22)	(0.19)	(0.17)	(0.22)
$FCFF$	**−0.072**	**−0.020**	**0.105**	**−0.060**	**−0.007**	**0.120**
	(0.12)	(0.11)	(0.14)	(0.12)	(0.11)	(0.14)
SOE	**0.080**	**0.176****	**0.359*****	**0.085**	**0.181****	**0.366*****
	(0.10)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)
GDP	**−0.152**	**−0.084**	**−0.238****	**−0.152**	**−0.083**	**−0.237****
	(0.11)	(0.09)	(0.12)	(0.11)	(0.09)	(0.12)
Constant	**3.714*****	**2.635****	**10.831*****	**3.709*****	**2.629****	**10.826*****
	(1.22)	(1.09)	(1.39)	(1.22)	(1.09)	(1.39)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
No. of obs.	11,162	11,163	11,161	11,162	11,163	11,161
R-squared	0.184	0.162	0.111	0.184	0.161	0.110

Table 7
Robustness tests

This table presents the results of additional tests and robustness checks based on a sample of 1,977 firms over the 2012-2018 period. Panel A reports potential differential effects of QFIIs' decarbonization on firms operate in coastal provinces and firms operate in inland provinces. Panel B shows potential differential effects of QFIIs' decarbonization on firms with QFIIs separately domiciled in Europe, Americas, as well as Asian and Australasia. Panel C repeats the analysis in Table 2 using an alternative linear measure of $QFII$, which is defined as the fraction of a firm's shares owned by QFIIs in a fiscal year. The first dependent variable ($CO2/Revenue$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total revenue at the end of the year. The second dependent variable ($CO2/Assets$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' total assets at the end of the year. The third dependent variable ($CO2/MV$) is computed as firms' annual carbon emissions ($Scope1, 2\ and\ 3$) measured in equivalents of metric tons of CO_2 divided by firms' market capitalization at the end of the year. All control variables are included but not shown for brevity, which are the same as the ones in the baseline test. All models control for year, industry and region fixed effects. All explanatory variables are lagged by one year. All continuous variables are winsorized at the levels of 1% and 99%. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

Panel A: Heterogeneous effects by firms' geographic location

	Coastal province	Inland province	Coastal province	Inland province	Coastal province	Inland province
	(1)	(2)	(3)	(4)	(5)	(6)
	$CO2/Revenue$		$CO2/Assets$		$CO2/MV$	
$QFII$	**−0.407*****	**−0.640*****	**−0.314*****	**−0.514*****	**−0.408*****	**−0.694*****
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.09)
Difference:	**0.233***		**0.20**		**0.286***	
Coastal – Inland	***Z-statistic = 2.77***		***Z-statistic = 2.42***		***Z-statistic = 2.83***	
Other controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
No. of obs.	6,728	4,434	6,729	4,434	6,729	4,432
R-squared	0.166	0.223	0.148	0.196	0.085	0.164

Table Continued Overleaf

Table 7 (Continued)

Panel B: Heterogeneous effects by QFIIs' geographic location

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)
$QFII_Europe$	**−0.391*****	**−0.300*****	**−0.386*****
	(0.10)	(0.09)	(0.11)
$QFII_Americas$	**−0.574*****	**−0.446*****	**−0.580*****
	(0.16)	(0.14)	(0.19)
$QFII_Asia$	**−0.602*****	**−0.499*****	**−0.670*****
$and\ Australasia$	(0.09)	(0.08)	(0.11)
Other controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Region FE	YES	YES	YES
No. of obs.	11,162	11,163	11,161
R-squared	0.184	0.161	0.110

Panel C: Alternative measure of foreign shareholding

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$QFII$	**−0.163****	**−0.110***	**−0.147****	**−0.157****	**−0.112***	**−0.157****
	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)
$FirmSize$	**−0.728*****	**−0.587*****	**−0.728*****	**−0.731*****	**−0.595*****	**−0.738*****
(orthogonalized)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)
$Leverage$	**1.760*****	**−0.018**	**0.947***	**1.058****	**−0.097**	**0.877**
	(0.42)	(0.36)	(0.50)	(0.46)	(0.40)	(0.54)
PPE	**−0.612****	**−0.132**	**−0.430**	**−0.747*****	**−0.097**	**−0.269**
	(0.26)	(0.23)	(0.30)	(0.28)	(0.25)	(0.32)
ROA	**−3.258*****	**−2.145*****	**−3.846*****	**−3.608*****	**−2.182*****	**−3.848*****
	(0.82)	(0.73)	(0.89)	(0.82)	(0.74)	(0.89)
BM	**−0.207****	**−0.169***	**0.867*****	**−0.246****	**−0.201****	**0.800*****
	(0.10)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)
$Growth$	**−0.119****	**−0.027**	**−0.058**	**−0.117****	**−0.023**	**−0.050**
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
$BoardSize$	**0.233**	**0.215**	**0.314**	**0.220**	**0.225**	**0.351**
	(0.19)	(0.17)	(0.22)	(0.19)	(0.16)	(0.22)

Table Continued Overleaf

Table 7 (Continued)

	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$	$CO2/Revenue$	$CO2/Assets$	$CO2/MV$
	(1)	(2)	(3)	(4)	(5)	(6)
$Growth$	**−0.145*****	**−0.044**	**−0.089**	**−0.122****	**−0.029**	**−0.061**
	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.05)
$BoardSize$	**0.329**	**0.305***	**0.449***	**0.229**	**0.211**	**0.309**
	(0.21)	(0.18)	(0.24)	(0.19)	(0.17)	(0.22)
$FCFF$	**−0.061**	**−0.008**	**0.120**	**−0.105**	**−0.024**	**0.101**
	(0.12)	(0.11)	(0.14)	(0.12)	(0.11)	(0.14)
SOE	**0.081**	**0.177****	**0.359*****	**0.062**	**0.166***	**0.350*****
	(0.10)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)
GDP	**−0.153**	**−0.084**	**−0.239****	**−0.154**	**−0.069**	**−0.243****
	(0.11)	(0.09)	(0.12)	(0.10)	(0.09)	(0.12)
Constant	**3.653*****	**2.578****	**10.766*****	**3.935*****	**2.341****	**10.657*****
	(1.22)	(1.09)	(1.39)	(1.19)	(1.08)	(1.37)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO
Region FE	YES	YES	YES	NO	NO	NO
No. of obs.	11,162	11,163	11,161	11,162	11,163	11,161
R-squared	0.184	0.161	0.110	0.192	0.165	0.116